

VU Research Portal

Training and low-pay mobility

Pavlopoulos, Dimitris; Muffels, Ruud; Vermunt, Jeroen K.

published in

Labour
2009

DOI (link to publisher)

[10.1111/j.1467-9914.2008.00438.x](https://doi.org/10.1111/j.1467-9914.2008.00438.x)

document version

Early version, also known as pre-print

[Link to publication in VU Research Portal](#)

citation for published version (APA)

Pavlopoulos, D., Muffels, R., & Vermunt, J. K. (2009). Training and low-pay mobility: The case of the UK and the Netherlands. *Labour*, 23(s1), 37-59. <https://doi.org/10.1111/j.1467-9914.2008.00438.x>

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal ?

Take down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

E-mail address:

vuresearchportal.ub@vu.nl

Training and low-pay mobility. The case of the UK and the Netherlands

Dimitris Pavlopoulos* Ruud Muffels Jeroen K. Vermunt

Abstract

This paper investigates the effect of training on low-pay mobility in the UK and the Netherlands. Our main contribution is the estimation of the 'true' effect of training by correcting for measurement error and transitory fluctuations - random shocks - of earnings. Our results indicate that in both countries, training increases the likelihood for moving from low to higher pay, while it reduces the likelihood for a transition from higher pay to low pay. In the UK, work-related and firm-specific training programmes but not general training programmes pay-off better for the intermediate- and the higher-educated workers. For the low-educated workers, no effect of training is found. The low skilled seem to gain less than the high skilled from firms' investments in human capital.

Keywords: Low pay, training, measurement error, Markov models.

JEL-code: J31, C23.

*Corresponding author: Dimitris Pavlopoulos, CEPS/INSTEAD and University of Leuven, OE CeSO, Parkstraat 45, 3000 Leuven, Belgium, tel. +32 16 323151, email: dimitris.pavlopoulos@ceps.lu. We are thankful to an anonymous reviewer as well as to the participants of the LoWER workshop in 2008 in Berlin to for their useful comments and suggestions.

1 Introduction

The issue of low-pay mobility is receiving increasing interest in the economic and political debate (OECD, 1996, 1997, 2003; Acemoglu, 2003b, 2003a). Low-pay mobility may have an equalizing effect on the earnings of workers at the bottom of the wage distribution. Specifically, the higher the level of upward low-pay mobility, the greater the chances for the low-wage workers to improve their earnings level in their career. The earnings mobility opportunities of workers is believed to increase by policies that enhance the participation in in-firm training programmes. This is also suggested by human capital theory which states that investments in training and education pay-off for people's life-time earnings (Becker, 1975). Through training, low-paid workers may improve their skills and their productivity and therewith increase their wage in the same or in a different job. Previous research suggests that training has a positive effect on wages, especially when the worker stays in the same job (see section 2). However, the effect of training on low-pay mobility has not been explicitly investigated.

Moreover, studies on low-pay mobility typically do not control for measurement error or for the fact that some of the true observed mobility is completely transitory, i.e. caused by random shocks, and therefore, it is not explained by the economic process. It is well known that the presence of measurement error in income data from household surveys results into severe overestimation of mobility (Hagenaars, 1994; Pischke, 1995; Gottschalk, 2005). Rendtel et al. (1998) find that approximately half of the observed poverty transitions from the German Socio-Economic Panel (GSOEP) are spurious. Besides the overestimation of average mobility, measurement error underestimates the effect of the usual covariates of earnings (Bound et al., 2001). When failing to control for classification error, the dependent variable in an earnings transition model contains noise. As a result, the effect of covariates in such a model will, most probably, be underestimated.¹ The effect of the presence of 'randomness' in low-pay mobility is similar to measurement error. If a person's wage is under the low-pay threshold but lies still very close to it, then even a light 'churning' in the wage distribution - unrelated to any individual factors, such as experience accumulation or job change - may turn the wage above the threshold. In this way, overall low-pay mobility increases and the effect of the covariates on earnings is attenuated.

¹This is not always the case. It rather depends on whether there is error in the measurement of the covariates and on whether this error is correlated with the error in the earnings.

The aim of this paper is to investigate the effect of training on low-pay mobility, accounting for measurement error and 'randomness' in mobility patterns. For this purpose, we develop a panel multinomial logit model for low-pay transitions with a latent structure that corrects for measurement error. The model is a Mixed Latent Markov model that is advancing the model of Rendtel et al. (1998). While Rendtel et al control for measurement error in aggregate transition probabilities, we also correct for observed and unobserved heterogeneity, and moreover, we use much longer time series. In this way, we relax the unattractive property of population homogeneity that is assumed in most studies using Markov models on labour market transitions. In our analysis, we distinguish among three states, namely, low-paid, higher-paid and the state of non-employment. For low pay, we apply the most common definition which is also used by the OECD: the threshold is set to the two-thirds of the median wage (OECD, 1996). The analysis is performed in two countries with rather different labour markets and training practices: the UK with a liberal-unregulated labour market and the Netherlands with a semi-regulated labour market. Following the predictions derived from the Varieties of Capitalist (VOC) approach (Hall & Soskice, 2001), we assume that training practices will differ markedly across the two regimes. The VOC approach distinguishes between liberal or unregulated market economies (LME) and regulated or coordinated market economies (CME) that are believed to be in sharp contrast with respect to wage setting and skill formation. The CME's are expected to focus on developing specific skills at the industry or the company level, coordinated wage bargaining and strong employee representation, whereas LME's are featured by low investments in training and skill formation, investments in general skills more than in firm-specific skills and flexible wages, reflecting more closely individual productivity, general education and work experience (Soskice, 2005). Therefore, we hypothesize that the unregulated British labour market invests less in skill formation than the coordinated Dutch labour market, and that the UK may be characterized as a 'general skills regime', whereas the Netherlands as a 'specific skills regime'. First, we investigate the effect of training incidence in the UK and the Netherlands. In a second step, we restrict our analysis to the UK to account for the effect of different types of training - job-related or firm-specific training and general training - as well as for the effect of the duration of the training programme.

The paper is organized as follows. Section 2 discusses the literature on the relationship between training and earnings. Section 3 elaborates on the model we apply. Section 4

presents the two datasets that we use. In section 5, we discuss the results of our analysis. Finally, section 6 concludes and presents some issues for further research.

2 The relationship between training and earnings

The relationship between human capital and earnings is well documented in economics (see, for example, Becker, 1962; Mincer, 1986). Standard economic theory suggests that there are two types of human capital that affect earnings formation. These two types are general human capital which concerns skills that a worker accumulates from education and from labour market experience, and firm-specific human capital which refers to skills that a worker acquires on the job and are usually not transferable across employers. General education and formal vocational training provide skills that increase the productivity of the worker throughout his working career. However, the effect of short-term training programmes is ambiguous. Some of them provide skills and qualifications that the worker can transfer from job to job, but others - especially on-the-job training programmes - provide skills that are job or firm-specific. Human capital theory predicts that training has a negative effect on earnings during the period of training provision, as the worker bears the costs, and a positive effect thereafter, as the worker increases his productivity using the new skills he acquired from training.

Empirical evidence is rather in accordance with the predictions of the theory. Mincer (1988) finds that American workers who received training have 4-6% higher wage growth than the rest of the workers. He also finds that training creates steeper wage profiles, regardless of whether the worker changes a firm or not. Parent (1999) suggests that there are wage gains from training for young American workers and these gains are transferable across employers. Booth (1991) suggests that wages of British male workers are 11.2% higher when receiving training. For the female workers, the training premium is even higher, namely, 18.1%. Lynch (1992) distinguishes between off-the-job and on-the-job training of young workers in the US. She finds that previous off-the-job training, previous apprenticeship and current on-the-job training increase wages. Moreover, she suggests that there is quite some heterogeneity in the returns of training. These returns are higher for the average and highly educated as well as for the unionized workers. Duncan and Hoffman (1979) find that in the US, the returns to training are rather uniform between men and

women as well as between native and immigrant workers. Nevertheless, they suggest that differences in the amount of training account for as far as 20% of the earnings gap between black and white workers and 10% of the earnings gap between male and female workers. For the Netherlands, Leuven and Oosterbeek (2002) find no effect of training on earnings, suggesting that the typical effect found in the relevant studies is actually due to unobserved characteristics.

Studies that investigate low-pay mobility use training as a covariate despite the fact that their focus has never been on training per se. For the UK, Sloane and Theodossiou (1996) find that recent training increases the probability for a low-to-higher pay transition. Similarly, Stewart and Swaffield (1999) find that in the UK, training reduces the probability of remaining in low pay by 5-10%. Blázquez Cuesta and Salverda (2007) reach the same conclusion for the Netherlands. They also find that the incidence of training is lower for the low-paid workers than for their higher-paid colleagues. However, no study has ever focused explicitly on the effect of training on low-pay mobility. Moreover, almost all the papers which study the effect of training on wages consider only the training programmes that the individual received, while being employed. Crucially, we extend this type of analysis by including training while being unemployed.

At the country level, labour market institutions play an important role in determining the provision and the characteristics of training. Acemoglou and Pischke (1998) suggest that the more compressed the wage distribution in a country the higher the incentives to firms to provide training and to share the training costs with their workers. When employers face binding wage regulations, they prefer to increase the productivity of their workers by providing them training opportunities. This reasoning resembles the assumptions of the VOC approach that were mentioned in the introduction. Specifically, in the VOC approach, McCall and Orloff (2005) argue that employers in specific skills regimes invest more in firm-specific training to increase productivity than employers in general skills regimes, as turnover is more costly for the former. From the two countries under scrutiny, the Netherlands may be characterised as a specific skills regime, while the UK as a general skills regime. In more detail, the Netherlands is a country with a coordinated but branch-level organised wage bargaining, more regulated employment relations and a stronger engagement of trade unions in the organisation of work-related or firm-specific training at the industry/branch level (Leisink & Greenwood, 2007). Training arrange-

ments are very often part of the wage bargaining or the collective labour agreements at the branch level, or CAOs, as they are called. Training programmes are typically carried out in formal educational settings and are usually longer in duration compared to the UK (OECD, 1999). However, there is firm heterogeneity in the provision of training. Large firms and firms within the service sector (mainly, banking and insurance) are most likely to offer training opportunities (van Loo & de Grip, 2003). On the contrary in the UK, firm-specific training is of little importance and trade unions are hardly ever involved and exert little influence on company's training programmes. Though training is carried out within the company, the size of the investments in training offered to workers is rather low due to their short duration (Blundell et al., 1996; OECD, 1999). Previous empirical findings show that training incidence is higher in the UK than in the Netherlands, but the total amount of training that individuals receive is larger in the Netherlands than in the UK (OECD, 1999; Pischke, 2001; Arulampalam et al., 2004).

In this paper, we focus on the effect of training on low-pay mobility. We consider all training programmes that were followed in the year prior to the survey, regardless of whether the individual was employed or not during the training period. In a second step, we distinguish between job-related or firm-specific training and general training, and we investigate the effect of the duration of training.

3 A Mixed Latent Markov model

Specification of the model

Our aim is to investigate the effect of enrolment in training on the year-to-year transitions from- and to low pay. More specifically, we want to study the effect of training on 'real' low-pay mobility, i.e. low-pay mobility net of measurement error and transitory fluctuations due to random shocks. Therefore, we start from a random-effects multinomial logit model and we impose a latent structure in the framework of the Latent Markov models (van de Pol & Langeheine, 1990; Langeheine & van de Pol, 1990; Vermunt et al., 1999; Bassi et al., 2000). The simplest form of this model is depicted in Figure 1. According to this model, the true state X_{it} of an individual i at a time point t cannot be observed; it is a latent state. We rather observe state Y_{it} , which might differ from the true (latent)

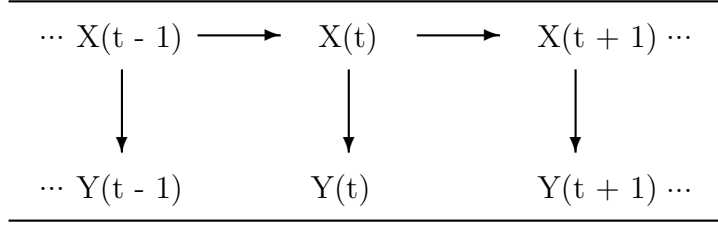


Figure 1: Path diagram for the Latent Markov model

state X_{it} . Y_{it} and X_{it} are probabilistically related.² The observed states at different time points are mutually independent, conditional on the true latent states. In other words, we assume that measurement error is not serially correlated in any way. This means that the independent classification error (ICE) assumption is made (Bassi et al., 2000). The true state X_{it} follows a Markov process. Thus, the state of an individual i at time point t , X_{it} , is independent of the state at time point t' , $X_{it'}$, where $t' < t - 1$, conditionally on the state at $t - 1$, X_{it-1} . An arrow indicates a direct effect, for example, the effect of the state at one time point on the state at the next time point. In our study, X_{it} and Y_{it} are the

²To understand how this model estimates measurement error, we present an example from Pavlopoulos (2007). Let us assume a fictitious transition matrix for a discrete variable X with two categories and between two time points. We further assume that there is error in the observation of the variable X . Instead of X_1 and X_2 , we rather observe the states Y_1 and Y_2 . The model for the joint distribution of Y_1 and Y_2 has the form of a Latent Class model for two time points. More specifically, the joint distribution of the observed states Y_1 and Y_2 can be expressed as follows:

$$P(Y_1 = y_1, Y_2 = y_2) = \sum_{X_1, X_2} [P(X_1 = x_1)P(X_2 = x_2|X_1 = x_1) P(Y_1 = y_1|X_1 = x_1)P(Y_2 = y_2|X_2 = x_2)] . \quad (1)$$

In the above probability expression, $P(X_1 = x_1)$ denotes the probability of being in the latent (true) state x_1 at the first time point and $P(X_2 = x_2|X_1 = x_1)$ the probability of being in the latent state x_2 at the second time point, conditional on being in the latent state x_1 at the first time point. The other two terms refer to the relationship between the latent and observed states, and represent the measurement error component. $P(Y_1 = y_1|X_1 = x_1)$ denotes the probability of observing the state y_1 conditional on being in the latent (true) state x_1 . The expected observed transition probability is:

$$P(Y_2 = y_2|Y_1 = y_1) = \frac{P(Y_1 = y_1, Y_2 = y_2)}{P(Y_1 = y_1)} = \frac{P(Y_1 = y_1, Y_2 = y_2)}{\sum_{Y_2} P(Y_1 = y_1, Y_2 = y_2)} . \quad (2)$$

To illustrate the impact of measurement error, assume that $P(X_2 = x_2|X_1 = x_1) = .05$ for $x_1 \neq x_2$ and that $P(Y_1 = y_1|X_1 = x_1) = P(Y_2 = y_1|X_2 = x_2) = .05$ for $y_1 \neq x_1$ and $y_2 \neq x_2$. Using equations (1) and (2) one can easily verify that the probability $P(Y_2 = y_2|Y_1 = y_1)$ for $y_1 \neq y_2$ equals .136 . In other words, even a small amount of classification error (5%) results in a large increase in the number of the observed transitions, here by a factor of 2.72 (13.6% observed versus 5% real transitions).

true and observed earnings states, respectively. These states are assumed to take on three values: low-paid, higher-paid and non-employed ('other').³

The joint probability of having a particular state path conditional on covariate values can be expressed as:

$$\begin{aligned}
 P(\mathbf{Y}_i = \mathbf{y}_i | \mathbf{Z}_i) &= \int \sum_{x_0=1}^3 \sum_{x_1=1}^3 \dots \sum_{x_T=1}^3 P(X_{i0} = x_0 | \mathbf{Z}_{i1}, F_i) \\
 &\quad \prod_{t=1}^T [P(X_{it} = x_t | X_{it-1} = x_{t-1}, \mathbf{Z}_{it}, F_i)] \\
 &\quad \prod_{t=0}^T P(Y_{it} = y_{it} | X_{it} = x_t) f(F_i) dF_i, \tag{3}
 \end{aligned}$$

where $i = 1, \dots, I$ is the index for the individual, $t = 0, \dots, T$ represents the time points and $f(F_i)$ is the joint density function for the individual effects F_i .

For identification reasons, we restrict the probability of observing a state Y_{it} conditional on the true state X_{it} to be constant over time, so $P(Y_{t-1} = s | X_{t-1} = r) = P(Y_t = s | X_t = r)$ for every t . With these restrictions, the model is identified when at least three time points are observed (Vermunt et al., 1999).

The literature points to two major issues when using Markov models for low-pay mobility: the need to control for heterogeneity (Shorrocks, 1976) and the need to control for initial conditions (see, for example, Cappellari & Jenkins, 2004). We control for observed heterogeneity with the approach suggested by Vermunt et al. (1999). Specifically, we allow the covariates \mathbf{Z}_{it} to affect the latent transition probabilities between latent states X_{it-1} and X_{it} . These covariates are assumed to be uncorrelated with the error. As mentioned earlier, to control for unobserved heterogeneity, we use the standard random-effects approach. As far as the issue of initial conditions is concerned, our model estimates the probability of being in a state in the initial time point $P(X_{i0} = x_0 | \mathbf{Z}_{i1}, F_i)$ and assumes perfect correlation between the unobserved effects that affect the initial state and the unobserved effects which affect the latent transition probability.

The probability $P(Y_{it} = y_{it} | X_{it} = x_t)$ represents the measurement or classification error.

³It is obvious that our definition of earnings states includes a state where the individual has no income from paid employment, the 'other' or non-employment state. For reasons of simplicity, however, we will refer to these states as 'earnings states', though with zero or little earnings.

However, this model does not only filter out measurement error. What the model actually does is to derive a pattern of ‘regular transition behaviour’ for individuals that belong to state x from the longitudinal information for all individuals (Vermunt, 2004). A spurious transition results into a violation of the first-order Markov process. However, a true but ‘unexpected’ transition may also be classified as spurious. This may be the case if the position of the worker in the wage distribution in $t - 1$ was so close to the low-pay threshold that a small overall change in the distribution moves him above this threshold in t . Thus, the ‘true’ transitions we estimate are the transitions between the states x_j and x_k , when accompanied by a change in the transition ‘behavior’; i.e. a change in the transition ‘behaviour’ of individuals in state x_j to the transition ‘behaviour’ of individuals in state x_k . A further discussion on the validity of this model can be found in Pavlopoulos (2007).

Parameter estimation

The estimates for the parameters of our model are obtained by means of maximum likelihood. Specifically, we use a variant of the well-known Expected Maximization (EM) algorithm (Dempster et al., 1977), which switches between an E step and a M step until it achieves convergence. The E-step of the EM algorithm involves computing the expected value of the complete data log-likelihood or, more intuitively, filling in the missing data (here the unobserved class memberships and the unobserved random effects) with their expected values given the current parameter values and the observed data. In the M step, standard estimation methods are used to update the model parameter, such that the expected complete data log-likelihood is maximized. In our case, the M step involves using the filled-in expected values as if these were observed in a standard logistic regression analysis. The E and M steps cycle until a certain converge criterion is reached.

The relevant variant of EM, which is called the forward-backward or Baum-Welch algorithm, is implemented in the recent syntax version of the statistical software LatentGOLD (Vermunt & Magidson, 2008). The standard EM algorithm cannot be applied for Latent Markov models for many time points T , as the time and storage needed for computation increases exponentially with T (Vermunt et al., 1999). The extended version of the forward-backward algorithm that we apply supports control for unobserved heterogeneity and multivariate analysis. These are features that are required for our analysis. Details on

this algorithm can be found in Vermunt et al. (2008).

4 Data and main concepts

The study uses data for the period 1991-2004 from two national panel datasets. For the UK, we use waves 1 to 14 of the British Household Panel Survey (BHPS) (Taylor et al., 2006), covering the years 1991-2004. For the Netherlands, our data come from the Socio-Economic Panel (SEP) (CBS, 1991). We make use of the last 9 waves of the panel, covering the years 1994-2002.⁴

As we focus on earnings transitions of employed individuals, our sample consists of prime age males (aged 25-55). The main reason for restricting our analysis to male employees is that females tend to have more career breaks and more intermittent periods of temporary or permanent layoff for very different reasons than males, such as caring obligations. Thus, we cannot include women in our analysis without controlling for the factors responsible for their different career paths, which goes beyond the scope of this paper. Our main economic variable is the earnings state of the individual, defined as the level of the hourly wage. As there is no direct information available on an individual's hourly wage, this is computed by dividing the earnings of last month from paid employment by the total amount of the monthly hours worked. Unusual overtime pay and bonuses are not included in the earnings of last month.

We define two real earnings states, low paid and higher paid, as well as an 'other' (non-employment) state. In more detail, the individuals that report paid employment as their main employment status are classified in one of the two earnings states. The self-employed are clustered in the 'other' state (non-employment state). Individuals who are in education, in unemployment or in inactivity are also classified as non-employed. This means that the 'other' state is very heterogeneous. This implies that transitions to and from 'other' cannot be expected to have a clear interpretation. However, the inclusion of such a state in our dependent variable is important from both a substantial and methodological point of view. Several studies, such as Cappellari and Jenkins (2004) and Stewart (2007) show that transitions to non-employment are common for low-paid workers. Moreover,

⁴The BHPS data were made available by the Data Archive at Essex University. The SEP was made accessible by Statistics Netherlands.

ignoring the non-employment state would make it impossible to define a Latent Markov model as the latent states should not only be mutually exclusive but also exhaustive.

Table 1: The distribution of the sample (in percentages)

		UK	Netherlands
Married		67.4	74.2
Age (mean)		39.2	40.2
Experience (mean in months)		241	
Education	Low	20.2	30.2
	High school	28.8	43.5
	Higher	51	26.3
Training			9.5
	Job-related	11.3	
	General	16.7	
Cases		7,884	4,214

The two datasets that are used include detailed information on training practices. From the BHPS, for the first 7 waves, we use the question 'Since September 1st last year, have you taken part in any education or training, other than training that was part of any job you may have?'. For the rest of the waves, we use the question, 'Have you taken part in any other training schemes or courses at all since September 1st (of the previous year) or completed a course of training which led to a qualification?'. In the BHPS, there is also information that allows the distinction between job-related or firm-specific and general training as well as the identification of the duration of the enrolment in the training programme. Following the BHPS questionnaire, we define training as 'job-related' or 'firm-specific', if the purpose of following the training programme was 'induction for current job', 'increase skills for current job' or 'improve skills for current job'. When the individual reports another purpose for following training than the aforementioned purposes, we define training as 'general'. In the SEP, we create our training variable using the following question about training programmes that individuals follow at the time of the survey: 'At this moment are you following an educational or other course in a school, in a training institute or in the firm you are working?'. As we are interested in the effect of

completed training programmes, we derive information on training in year t from the survey in year $t - 1$. Finally, in both datasets, the relevant questions refer to all types of courses, both part-time courses and full-time programmes. The distribution of our estimation sample is given in Table 1. This table includes all the covariates that we include in our multivariate analysis.

Each individual is included in the analysis from the time point he first enters the survey. Using maximum likelihood estimation with missing data, we deal with the fact that at some occasions information for the earnings state of the individual may be missing, due to non-response or temporary attrition. This approach does not cause any bias as long as non-response is random conditionally on observed values, that is, as long as the missing data is missing at random (MAR). Missing values in covariates were imputed by interpolation when possible.⁵ The remaining missing values were imputed by the mean of the relevant variable.

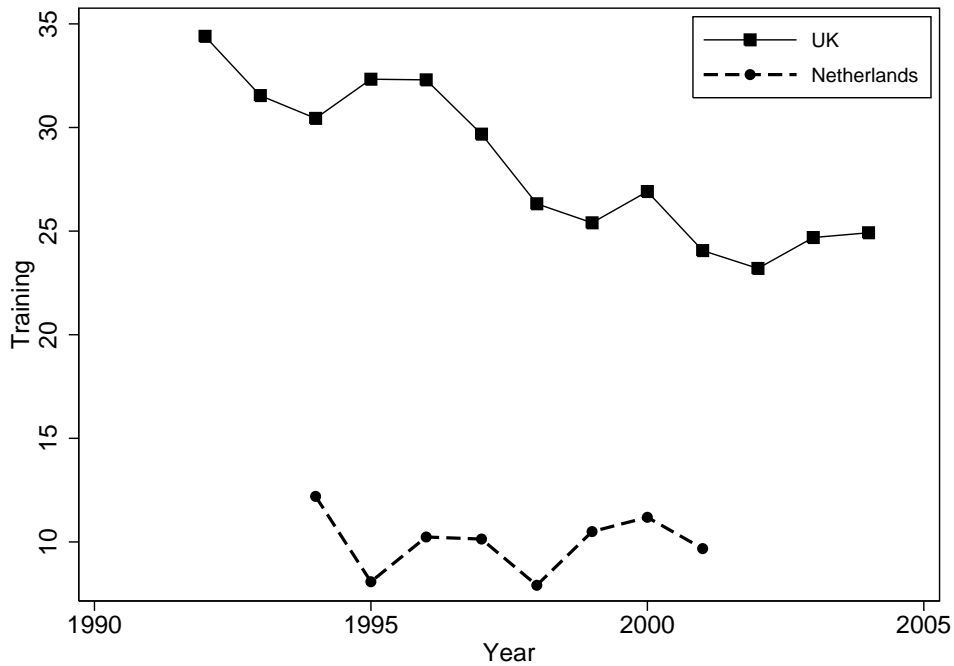


Figure 1: Training incidence across countries in percentages.

⁵For example, if the individual reported ‘higher education’ in $t - 1$ and $t + 1$, and the value for education was missing for t , we imputed the value for education in t as being ‘higher education’.

5 Results

Some descriptives

The incidence of training over time is depicted in Figure 1. The percentage of workers that receive training is unexpectedly higher in the UK than in the Netherlands. Specifically, in the UK, 23.5-34.4% of male employees go through some type of training every year. However, the percentage of trainees decreases over time. In the Netherlands, the incidence of training varies between 8% and 11.9% but without any clear trend. These findings are in accordance with Arulampalam et al. (2004).

Table 2: Low-pay mobility conditional on training incidence (in percentages)

State in t	UK			Netherlands		
	no training	training	Total	no training	training	Total
Low pay	53.3	45.6	51.7	48.5	39.78	47.47
Higher pay	36.9	48.2	39.4	2.92	54.84	44.32
Other	9.7	6.2	8.9	8.58	5.38	8.21
Total	100	100	100	100	100	100
Pearson (prob)	30.07 (0.000)			4.97 (0.083)		
Cases	2,316	702	3,018	669	93	792

Note: This table presents the distribution of individuals that were in low pay in year $t - 1$ in destination states in year t according to whether they received training between the time point $t - 1$ and t .

Table 2 presents some descriptives on the effect of training on low-pay mobility. In both countries, the percentage of low-paid workers that pass the low-pay threshold in a period of one year is higher for those that have followed a training course. In the UK, 48.2% of the low-paid workers that received training moved to higher pay, as opposed to only 36.9% of their colleagues that did not receive any training. In the Netherlands, 54.8% of the low-paid workers that finished a training course passed the threshold, as opposed to only 42.9% of those that did not follow a training course. The Pearson chi-square statistic shows

that the association between the earnings state and the training incidence is significant (in the Netherlands only at the 10% level). However, the association of training with low-pay mobility may just be capturing the effect of observed and unobserved heterogeneity. The multivariate analysis that follows will be more informative on this issue.

Table 3: Model comparison

	UK		Netherlands	
	LL	BIC (LL)	LL	BIC (LL)
1. Markov	-21,015.9	42,695.8	-9,260.6	18,894.3
2. Latent Markov	-20,205.3	40,966.9	-8,948.7	18,321.4
3. Mixed Markov	-20,612.4	41,763.2	-8,994.8	18,396.6
4. Mixed Latent Markov	-20,118.5	40,829.1	-8,925.3	18,308.6

Note: LL refers to the Log Likelihood and BIC (LL) refers to the Bayesian Information Criterion that is based on the Log Likelihood value.

Results of the multivariate analysis

In total, we applied four versions of the model described by equation (3); namely, a standard Markov transition multinomial logit model, a model with a latent structure (Latent Markov model), a model with random-effects (Mixed Markov), and a random-effects model with a latent structure (Mixed Latent Markov model) correcting for observed and unobserved heterogeneity. The second and the fourth model correct for measurement error. The Log-Likelihood values and the BIC values for all four models are reported in Table 3. This Table shows that Model 2 fits the data considerably better than Model 1. The same holds for Model 4 and Model 3, respectively. This indicates that correcting for measurement error is important, regardless of whether we control for observed and unobserved heterogeneity. Moreover, controlling for observed and unobserved heterogeneity improves the fit of the model, as can be seen by comparing the fit of either Models 1 and 3 or Models 2 and 4.

The estimates of training and other covariates from Models 3 and 4 are presented in

Table 4: Results from the Mixed Markov and the Mixed Latent Markov model

		UK		Netherlands	
	Transition	Without error correction	With error correction	Without error correction	With error correction
Training	low pay to higher pay	0.238**	0.287**	0.595**	0.826**
	low pay to other	-0.157	-0.380	-0.424	-1.526**
	higher pay to low pay	-0.328***	-0.304***	-0.306	-0.692
	higher pay to other	-0.172**	-0.243***	-1.805***	-1.959***
Education (ref. lower than high school)					
High school	low pay to higher pay	0.062	0.079	0.213	0.261
	low pay to other	0.119	-0.038	0.263	0.042
	higher pay to low pay	-0.072	-0.113	-0.704***	-1.164***
	higher pay to other	-0.044	-0.043	-0.356***	-0.342
Higher education	low pay to higher pay	0.466***	0.527***	1.041***	1.241***
	low pay to other	0.158*	0.245*	1.800***	1.527***
	higher pay to low pay	-0.746***	-0.803***	-1.557***	-2.124***
	higher pay to other	-0.160***	-0.087	-0.364**	-0.340**
Experience (Age for the Netherlands)	low pay to higher pay	-0.070	0.026	0.011	0.037
	low pay to other	-0.713***	-0.894***	0.005	0.031*
	higher pay to low pay	-0.515***	-0.567***	-0.043***	-0.088***
	higher pay to other	-0.703***	0.871***	-0.004	-0.003
Cases		7,884	7,884	4,214	4,214

* significant at 10%; ** significant at 5%; *** significant at 1%

The dependent variable is the earnings state. It takes three values: low pay, higher pay and other. Transitions between all states are modelled. However, here we only present the estimates on the transitions from low to higher pay, from low to the 'other' state and from higher to low pay. The control variables are calendar time, marital status, age, age squared, experience squared (only in the UK). Other job characteristics are not included as covariates as these are not observed for the individuals being in the 'other' state and therefore their inclusion would make estimation of the model unfeasible.

Table 4. One commonly-used specification is to allow covariates to affect the probability of being in a certain state at a time point t . We use another more flexible specification in which covariates exert an effect on making a particular type of transition. For example, the model estimates the effect of training on making a transition from low pay to higher pay rather than 'just' estimating the effect of training on being in low pay. Our model estimates the effect of training and other covariates on all six possible transitions between the three states (low pay, higher pay, other). In Table 4, we only present the estimates for the transitions from low pay and from higher pay to any other state, as these are the most important with respect to our research questions.

Our results show that training has a positive effect on the likelihood of a low-to-higher pay transition. In both countries, the relevant coefficient is positive. Results concerning

the likelihood of the opposite transition, i.e. a transition from higher pay to low pay, are consistent with the previous finding, as all coefficients are negative, although not always statistically significant. More specifically, in the UK, this effect is clear, as the relevant coefficient is statistically significant, while in the Netherlands, coefficients are negative but insignificant. As far as transitions from employment to non-employment are concerned, we find that in both countries, following a training course reduces the likelihood of moving out of employment. However, in the UK, only the coefficient for the higher pay to the 'other' state transition is significant. It seems, therefore, that training improves the employment prospects - or strengthens the work-oriented attitude, as we do not distinguish between quits and lay offs - both in the UK and the Netherlands.

The correction for measurement error and transitory earnings' fluctuations strengthens most of the effects. Comparing the estimates of model 3 and model 4, we see that most of the estimated coefficients of model 4 are larger than those of model 3. This difference in the coefficients was tested with a Hausman test and was found significant. This finding holds for the estimates of all covariates included in Table 4.

The results with respect to education are in accordance with economic theory. In both countries, having completed higher education increases the likelihood for a low-to-higher pay transition and decreases the likelihood for a higher-to-low pay transition compared to having completed low education. Having completed high-school education seems to have a similar effect, although most coefficients are insignificant. Concerning labour market experience, we find no significantly positive effect for transitions from low pay to higher pay. On the contrary, we find a negative effect of experience on the likelihood of moving from higher pay to low pay.⁶

Previous studies suggest that there are complementarities in the effect of training, education and labour market experience on earnings (Lynch, 1992). The presence of such complementarities in the effect of these variables on low-pay mobility was tested with the inclusion of several interaction effects between training and these variables.⁷ None of these interaction effects appeared significant. This suggests that such complementarities do not exist for low-pay mobility. At a first sight, this finding seems contradictory to previous studies. One may think that this is due to the fact that, so far, we have not distinguished

⁶For the Netherlands, we report the coefficients for age as a proxy for labour market experience. The Dutch Socio-Economic Panel does not allow to derive reliable information on labour market experience.

⁷The estimates for these interaction effects are not presented here, but are available on request.

between different types of training and have not taken into account the duration of the training programme. This issue is addressed in the following sub-section.

Table 5: Type and duration of training effects in the UK

		Model 4a	Model 4b	
Job-related training	low to higher	0.566		0.289
	low to other	0.363	Job-related training	-2.251***
	higher to low	0.496		-0.808***
	higher to other	-0.097		-1.654***
General training	low to higher	-0.150		0.241
	low to other	0.176	General training	-0.584
	higher to low	0.185		-0.427*
	higher to other	0.658***		0.001
High-school (ref. low)	low to higher	0.540***		0.612***
	low to other	0.164	High-school (ref. low)	0.206
	higher to low	-1.208***		-1.508***
	higher to other	-0.113		-0.155
Higher (ref. low)	low to higher	1.293***		1.631***
	low to other	0.674***	Higher (ref. low)	0.892***
	higher to low	-1.909***		-2.295***
	higher to other	-0.163		-0.213
Higher * job-related training	low to higher	0.103**	Duration * job-related training	0.212
	low to other	-1.677***		0.223
	higher to low	-1.753***		3.369
	higher to other	-1.029***		0.089
Higher * general training	low to higher	0.686	Duration * general training	0.161
	low to other	-2.930***		0.154
	higher to low	0.397		3.361
	higher to other	0.047		0.044
Cases		7,884	4,214	
Log-Likelihood		43,597	42,413.5	
BIC		21,089.2	20,452.6	

* significant at 10%; ** significant at 5%; *** significant at 1%

Models 4a and 4b are the same as the model that corrects for measurement error in Table 4. Model 4a includes the interaction terms between training and education, while Model 4b includes the interaction terms between the type of training and the duration of training.

Does the type and the duration of training matter?

In this sub-section, we refine the analysis of the previous part by distinguishing between job-related or firm-specific training and general training. Moreover, we account for the

effect of the duration of the training course. As the information on the type of the training course and the duration of training seems unreliable in SEP, we perform this analysis only for the UK. Specifically, we employ the same model as in the previous part (Model 4) using two versions of it. In the first version (which we name Model 4a), our variable 'training' takes three values: no training, job-related training and general training. In the second version (which we name Model 4b), we also control for the duration of the training course. Table 5 presents the results of these models. Note that only the models that correct for measurement error are presented in Table 5.

Table 5 shows that the type of training matters for low-wage mobility, while the duration of the enrolment in the training programme does not. Moreover, we find complementarities of job-related training with education. In more detail, only for the high-school graduates and the higher education graduates does job-related training increase the likelihood of a low-to-higher pay transition and decrease the likelihood of a higher-to-low pay transition. No significant effect is found for the low-educated workers. This finding is in accordance with previous research on the relationship between job-related training and earnings. General training has no significant effect on the likelihood of moving between low and higher pay for any group of workers.

On the other hand, the duration of the training programme does not affect the likelihood of moving from low to higher pay or vice versa. This result holds for both job-related or firm-specific training and general training programmes. Therefore, it seems that what matters for low pay mobility is the type of training and the person's level of education but not the duration of the enrolment in the training programme.

6 Conclusions and discussion

The aim of this paper was to investigate the effect of training on low-pay mobility in the UK and the Netherlands. We employed a modelling approach that enabled us to study the effect of training investments on low-pay mobility, net of measurement error and transitory moves out and into low pay due to random shocks. In contradistinction to previous studies, we investigated the effect of all training programmes, regardless of the employment status of the individual at the time of the training. For the UK, in a second step, we distinguished between different types of training programmes and moreover we

studied the effect of the duration of the training programme. Throughout our analysis, we distinguished between three states, low pay, higher pay and non-employment ('other'), and we used the most common definition of low-pay threshold, namely, the two-thirds of the median hourly wage. Our approach combined the virtues of a random-effects multinomial logit model and latent class modelling. The use of a random-effects model allowed us to control for unobserved heterogeneity.

Contrary to what economic theory suggests, it turns out that in the flexible British labour market, that is characterized by more turnover and wage inequality, training is more common than in the regulated Dutch labour market that is characterized by less turnover, low wage inequality and heavy involvement of trade unions in the organization of training at the industry-branch level. However, we should keep in mind that training in the UK refers to training programmes of short duration organized within the company. In the regulated Dutch labour market, training is less common than in the UK, but the longer enrolment in training implies that the size of the investment in training of the workers is probably larger than in the UK.

The results of our analysis indicate that training improves the chances for upward wage mobility for the workers of the lower segment of the wage distribution and reduces the risk of higher paid workers to move down the pay ladder and fall into low pay. In this respect, our results complement the findings of other studies in the field, suggesting that training improves earnings' prospects (Duncan & Hoffman, 1979; Booth, 1991; Lynch, 1992; Sloane & Theodossiou, 1996; Blázquez Cuesta & Salverda, 2007). In both countries, we found a strong positive effect of training on the likelihood of moving from low to higher pay. In the UK, we also found that training reduces the likelihood of a higher-to-low pay transition. Our study also verifies that besides training, general human capital in the form of formal education increases the chances of low-paid workers to improve their wage as well as to reduce the chances of higher paid workers to move down the pay ladder and fall into low pay. These findings seem to corroborate the predictions derived from human capital theory as well as the results of other studies in the field.

Previous studies suggest that the effect of training is not homogeneous across population groups. The access to training and the pay-off to training differ according to education, gender, age and immigrant status. At least in the UK, where the data allowed for it, we investigated for complementarities between education and different types of training. The

effect of training on low-wage mobility was found to depend on the type of the training and on the person's education level. Job-related or firm-specific training seems to pay-off, but only for workers at the intermediate and the higher education level. Training appears incapable of increasing the upward wage mobility chances of the lower-skilled workers. Therefore, the investments in human capital formation seem efficient in flexible labour markets, such as the UK, but only for the higher-skilled workers. This might reflect the typical features of a very flexible labour market where general training is dominant but pays-off less than firm-specific training. This asks for a shift in training policies in such countries so that the lower-paid workers can benefit more by job-specific investments in training that is offered within or outside the firm.

Appendix: Description of the variables

Education: This is the highest educational level completed by the individual. It can take three values, lower than high school, high school and higher education.

Training: It takes the value 1 when the individual received formal training during the year prior to the survey and 0 in all other cases.

Labour market experience: Measured in months. This is available only for the UK. It is constructed by combining data from the yearly files and the employment history files of BHPS.

Age: Measured in years.

References

- Acemoglou, D., & Pischke, J. S. (1998). Why do firms train? theory and evidence. *Quarterly Journal of Economics*, 63(1), 69-119.
- Acemoglu, D. (2003a). Cross-country inequality trends. *Economic Journal*, 113, 121-149.
- Acemoglu, D. (2003b). Patterns of skill premia. *Review of Economic Studies*, 70(2), 199-230.
- Arulampalam, W., Bryan, M. L., & Booth, A. L. (2004). Training in Europe. *Journal of the European Economic Association*, 2(2-3), 346-360.
- Bassi, F., Hagenaars, J. A., Croon, M. A., & Vermunt, J. K. (2000). Estimating true changes when categorical panel data are affected by uncorrelated and correlated classification errors. *Sociological Methods and Research*, 29(2), 230-268.

- Becker, G. S. (1962). Investment in human capital: A theoretical analysis. *The Journal of Political Economy*, 70(5, part 2), 9-49.
- Becker, G. S. (1975). *Human capital : a theoretical and empirical analysis, with special reference to education* (2nd ed.). New York: National Bureau of Economic Research with Columbia University Press.
- Blázquez Cuesta, M., & Salverda, W. (2007, January). *Low pay incidence and mobility in the Netherlands exploring the role of personal, job and employer characteristics*. Amsterdam Institute of Advanced Labour Studies, University of Amsterdam, Working Paper Number 06/46.
- Blundell, R., Dearden, L., & Meghir, C. (1996). *The determinants and effects of work-related training in Britain*. Institute for Fiscal Studies.
- Booth, A. L. (1991). Job-related formal training: Who receives it and what is it worth? *Oxford Bulletin of Economics and Statistics*, 53(3), 281-294.
- Bound, J., Brown, C., & Mathiowetz, N. (2001). Measurement error in survey data. In J. J. Heckman & E. Leamer (Eds.), *Handbook of econometrics* (Vol. 5, p. 3705-3843). Amsterdam: Elsevier.
- Cappellari, L., & Jenkins, S. P. (2004). Modelling low income transitions. *Journal of Applied Econometrics*, 19, 593-610.
- CBS. (1991). *Sociaal-economisch panelonderzoek. inhoud, opzet en organisatie*. Voorburg/Heerlen: Centraal Bureau voor de Statistiek.
- Dempster, A. P., Laird, N. M., & Rubin, D. B. (1977). Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society, Series B*, 39(1), 1-38.
- Duncan, G. J., & Hoffman, S. (1979). On-the-job training and earnings differences by race and sex. *Review of Economics and Statistics*, 61(4), 594-603.
- Gottschalk, P. (2005). Downward nominal-wage flexibility: Real or measurement error. *Review of Economics and Statistics*, 87(3), 556-568.
- Hagenaars, J. A. (1994). Latent variables in log-linear models of repeated observations. In A. von Eye & C. C. Clogg (Eds.), *Latent variable analysis: Applications for developmental research* (p. 329-352). Thousand Oaks, CA: Sage Publications.
- Hall, P. A., & Soskice, D. (2001). *Varieties of capitalism: The institutional foundations of comparative advantage*. Oxford/New York: Oxford University Press.
- Langeheine, R., & van de Pol, F. (1990). A unifying framework for markov modelling in discrete space and discrete time. *Sociological Methods and Research*, 18, 416-441.
- Leisink, P., & Greenwood, I. (2007). Company-level strategies for raising basic skills: A comparison of Corus Netherlands and UK. *European Journal of Industrial Relations*, 13(3), 341-360.
- Leuven, E., & Oosterbeek, H. (2002, January). *A new approach to estimate the wage returns to work-related training*. Institute for the Study of Labor (IZA), IZA DP No. 526.
- Lynch, L. M. (1992). Private-sector training and the earnings of young workers. *American Economic Review*, 82(1), 299-312.

- McCall, L., & Orloff, A. (2005). Gender, class, and capitalism. *Social Forces*, 12(3), 159-169.
- Mincer, J. (1986). Wage changes in job changes. In R. G. Ehrenberg (Ed.), *Research in labor economics* (Vol. 8, p. 171-197). Greenwich: JAI Press.
- Mincer, J. (1988). *Job training, wage growth and labor turnover*. NBER Working Paper.
- OECD. (1996). *Employment outlook 1996*. OECD.
- OECD. (1997). Earnings mobility: Taking a longer-run view. In *Employment outlook 1997* (p. 27-61). OECD.
- OECD. (1999). *Employment outlook 1999*. OECD.
- OECD. (2003). *Employment outlook 2003*. OECD.
- Parent, D. (1999). Wages and mobility: The impact of employer-provided training. *Journal of Labor Economics*, 17(2), 298-317.
- Pavlopoulos, D. (2007). *Wage mobility patterns in Europe*. Doctoral Dissertation, Tilburg University. Tilburg.
- Pischke, J.-S. (1995). Measurement error and earnings dynamics: Some estimates from the PSID validation study. *Journal of Business and Economic Statistics*, 13(3), 305-314.
- Pischke, J.-S. (2001). Continuous training in Germany. *Journal of Population Economics*, 14(3), 523-548.
- Rendtel, U., Langeheine, R., & Berntsen, R. (1998). The estimation of poverty dynamics using different measurements of household income. *Review of Income and Wealth*, 44(1), 81-98.
- Shorrock, A. F. (1976). Income mobility and the markov assumption. *Economic Journal*, 86, 566-578.
- Sloane, P. J., & Theodossiou, I. (1996). Earnings mobility, family income and low pay. *Economic Journal*, 106, 657-666.
- Soskice, D. (2005). Varieties of capitalism and cross-national gender differences. *Social Politics*, 12(2), 170-179.
- Stewart, M. B. (2007). The inter-related dynamics of unemployment and low-wage employment. *Journal of Applied Econometrics*, 22(3), 511-531.
- Stewart, M. B., & Swaffield, J. K. (1999). Low pay dynamics and transition probabilities. *Economica*, 66(127), 23-42.
- Taylor, M. F. e., Brice, J., Buck, N., & Prentice-Lane, E. (2006). *British Household Panel Survey User Manual volume A: Introduction, technical report and appendices*. Colchester: University of Essex.
- van de Pol, F., & Langeheine, R. (1990). Mixed markov latent class models. *Sociological Methodology*, 20, 213-247.
- van Loo, J., & de Grip, A. (2003). *Loont het investeren in het personeel?* Research Center for Education and the Labour Market, ROA-R-2003/1.
- Vermunt, J. K. (2004). Comment on: An analysis of classification error for the revised current population survey employment questions. *Survey Methodology*, 30, 141-144.
- Vermunt, J. K., Langeheine, R., & Böckenholt, U. (1999). Discrete-time discrete-state latent markov models with time-constant and time-varying covariates. *Journal of Educational and Behavioral Statistics*, 24, 178-205.

- Vermunt, J. K., & Magidson, J. (2008). *LG - syntax user's guide: Manual for Latent GOLD 4.5 syntax module*. Belmont Massachusetts: Statistical Innovations Inc.
- Vermunt, J. K., Tran, B., & Magidson, J. (2008). Latent class models in longitudinal research. In S. Menard (Ed.), *Handbook of longitudinal research: Design, measurement, and analysis* (p. 373-385). Burlington, MA: Elsevier.